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Testing the Factors Affecting Intraday Market Electricity Prices by Connectedness Approach[1]

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Gün İçi Piyasası Elektrik Fiyatlarını Etkileyen Faktörlerin Bağlantılılık Yaklaşımı ile Test Edilmesi[2]

Abstract

This study aims to dynamically analyse the relationship between intraday market electricity prices and day-ahead market electricity prices and the amount of electricity generated based on the primary energy resource in Turkey. In this context, the data set consisting of electricity prices in the day-ahead market, electricity prices in the day-ahead market, and electricity generation amount based on primary energy resources, covering the period from 1 January 2018 to 19 June 2022, was analysed with TVP-VAR. Findings reveal that the relationship between variables changes over time and is affected by global events. Furthermore, it has been determined that the intraday market has moved from a general receiver of volatility to a general transmitter in the post-Covid 19 period.

Keywords : Intraday Market, Electricity Price, Connectedness.

JEL Classification Codes : C32, Q40, Q42, Q47.

Öz

Bu çalışma, Türkiye'de birincil enerji kaynağına dayalı olarak üretilen elektrik miktarı ve gün içi piyasası elektrik fiyatları ile gün öncesi piyasası elektrik fiyatları arasındaki ilişkiyi dinamik olarak analiz etmeyi amaçlamaktadır. Bu kapsamda, 1 Ocak 2018-19 Haziran 2022 dönemini kapsayan, gün içi piyasası elektrik fiyatları, gün öncesi piyasası elektrik fiyatları ve birincil enerji kaynaklarına dayalı elektrik üretim miktarından oluşan veri seti TVP-VAR ile analiz edilmiştir. Bulgular, değişkenler arasındaki ilişkinin zaman içinde değiştiğini ve küresel olaylardan etkilendiğini ortaya koymaktadır. Ayrıca Covid 19 sonrası dönemde gün içi piyasasının volatilitenin genel alıcısı konumundan genel yayıcısı konumuna geçtiği tespit edilmiştir.

Anahtar Sözcükler : Gün İçi Piyasası, Elektrik Fiyatı, Bağlantılılık.

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[1] *This study has been developed from the paper titled "Gün İçi Piyasası Elektrik Fiyatlarını Etkileyen Faktörlerin Bağlantılılık Analiziyle Test Edilmesi", presented as oral and published as a full text at the 25th Finance Symposium held in Burdur/Turkey on 19-22 October 2022.*

[2] *Bu çalışma, 19-22 Ekim 2022 tarihinde Burdur'da gerçekleştirilen 25. Finans Sempozyumunda sözlü olarak sunulan "Gün İçi Piyasası Elektrik Fiyatlarını Etkileyen Faktörlerin Bağlantılılık Analiziyle Test Edilmesi", başlıklı tebliğin geliştirilmesi ile oluşturulmuştur.*

1. Introduction

Electrical energy, which is not found in nature and is defined as a secondary energy resource because it is obtained from various energy resources, is seen as an energy type that shows the countries' production level (Yılmaz & Cowley, 2022: 61). Accordingly, Turkey's demand for electrical energy also tends to increase. Turkish Electricity Transmission Corporation (TEİAŞ) electricity statistics shows that the generation of Turkey, which was approximately 240,000 GWh in 2012, increased by 38.3% in 2021 and reached 332,000 GWh. In this period, only in 2019, there was a decrease of 0.2% compared to the previous year. In 2020, measures taken in line with the Covid-19 Pandemic intensified, the rate of increase in electricity generation remained below 1%, and in 2021 it reached the rate of increase in 2017 with 8%.

On the other hand, due to the reforms in the electricity markets, generation, supply, transmission, and distribution were separated by laws numbered 4628 and 6446. As of 2022, over a thousand generation companies, over two hundred supply companies, and twenty-one distribution companies operate in the electricity market (EXIST Transparency Platform, 2022). TEİAŞ, on the other hand, is the institution responsible for the transmission of electricity (TEİAŞ, 2022). Today, electrical energy is seen as a commodity that can be bought and sold like other commodities (Girish & Vijayalakshmi, 2013: 70). Electricity is traded between generation and supply companies through bilateral agreements, spot markets and balancing power markets. Bilateral agreements can be made through the over-the-counter markets and the Power Futures Market operated by Energy Exchange Istanbul (EXIST, 2022a). On the other hand, the Day-Ahead Market (DAM) and Intraday Market within EXIST constitute the spot electricity markets. DAM is operated one day before the physical delivery of electrical energy, allowing the parties to balance their short/excess positions in addition to bilateral agreements (Yarıcı, 2018: 10-11). The Market Clearing Price formed in DAM is considered the reference price of electrical energy (Devir, 2017: 81). Acting as a bridge between the DAM and the Balancing Power Market, Intraday Market makes a significant contribution to the balancing of the positions of the market participants and the sustainability of the market (EXIST, 2022b). Market participants can bid separately for each hour of the day or certain hours in the intraday market (EXIST, 2022c). In addition to Market Clearing Price (MCP), primary electricity resources also play a decisive role in the bids given in the intraday market. These resources are divided into fossil and renewable energy resources. While coal, natural gas, oil, and nuclear are fossil resources, hydroelectric, wind, solar, geothermal, and biomass are renewable energy resources. This paper aims to reveal to what extent the changes in the intraday market electricity price are affected by the changes in MCP and the amount of electricity generation based on resources. In this context, the connectedness between the daily intraday market electricity prices and the MCP and primary energy resources was investigated by TVP-VAR.

2. Literature Review

Electrical energy has specific characteristics that distinguish it from other energy markets because it is an energy that cannot be stored economically (Thoenes, 2011: 2; Apergis et al., 2020: 1). Electricity prices show seasonality, return to the average, volatility, and jumps, as electrical energy must be consumed when it is generated. In addition, weather conditions such as a change in demand, temperature, precipitation, water reservoir levels, and the condition of the resource used in generation plants play a role in the behaviour of electricity prices (Girish & Vijayalakshmi, 2013: 70). Due to the characteristics of electricity prices depending on various factors, price forecasting, determinants, and volatility have become the subjects that have been frequently researched in the literature.

In recent years, many studies (Mirakyan, 2017; Bento et al., 2018; Kuo & Huang, 2018; Uğurlu et al., 2018; Xie et al., 2018; Zhou, 2019; Guo et al., 2020; Huang et al., 2020; Qiao & Yang, 2020; Li & Becker, 2021; Tschora et al., 2022; Yang et al., 2022) have been conducted on electricity price prediction with various statistics. Moreover, many studies (Cervone, 2014; Marcos et al., 2019; Ulgen & Poyrazoğlu, 2020; Matsumoto & Endo, 2021; Rajan & Chandrakala, 2021) have been conducted by artificial intelligence models that can learn the complex structure of electricity prices. In addition, studies in which volatility estimation for electricity prices was made (Zareipour et al., 2007; Chan et al., 2008; Karakatsani & Bunn, 2010; Ciarreta & Zarraga, 2016; Dong et al., 2019; Terzic et al., 2021; Niza et al., 2022) come to the fore in the literature.

Understanding the dynamics of electricity prices is as important as price forecasting and volatility estimation for electricity market participants. The typical result of the papers investigating the relationship between electricity prices and primary energy resources is that the increase in generation with renewable energy resources has a lowering effect on electricity prices in the day-ahead market (Würzburg et al., 2013; Pereira & Saraiva, 2013; Ketterer, 2014; Clo et al., 2015; Gürtler & Paulsen, 2018; Nieta & Contreras, 2020; Fernandez et al., 2021). Gürtler & Paulsen (2018) concluded that this situation is also valid in the EEX intraday market. In some papers (Pereira & Saraiva, 2013; Nieta & Contreras, 2020; Fernandez et al., 2021), the effect of generation with renewable resources on electricity prices was tested by simulation method. As a superior result, Fernandez et al. (2021) state that a 1% decrease in demand due to the increase in the generation of photovoltaic panels used in residences may reduce electricity prices in the Spanish day-ahead market by 2%. Clo et al. (2015) and Gürtler & Paulsen (2018) investigated the effect of solar and wind power plants on MCP in Italy and EEX electricity markets by regression method. They found that additional generation with these resources can reduce electricity prices in both markets.

On the other hand, by performing a regression analysis, Wurzburg et al. (2013) found that the merit order effect was at different levels in the German and Austrian electricity markets. Ketterer (2014) concluded with the GARCH model that the increase in wind power plant generation reduced electricity prices in the German day-ahead market and increased volatility. The merit order effect decreased over time. Paraschiv et al. (2014) examined the German day-ahead market prices with ARMAX and GARCH models. They concluded that generation from wind and solar power plants partially affects electricity prices. The sensitivity of the day-ahead market price to coal, gas, oil, and renewable energy resources changes over time. Berk & Tosun (2019) tested the relationship of electricity generation from wind farms with electricity prices in the Turkish day-ahead market with wavelet transform Granger causality analysis. They concluded that there is a negative causality relationship between wind farms and MCP, and this relationship's strength changes in different periods. Mulder & Scholtens (2013) determined by correlation analysis that electricity prices in the Dutch day-ahead market are affected by demand and gas prices, while the installed power of solar power plants does not change the average electricity prices. On the other hand, Asceric et al. (2022) concluded that the German day-ahead market prices correlate more with generation from fossil resources than renewable energy resources. Gianfreda et al. (2019) tested the effect of energy resources on electricity prices in Italy's day-ahead market and balanced power market by variance decomposition and impulse response function. They found that generation with renewable resources reduces the impact of fossil fuels on day-ahead market prices. Coal generation is more effective on electricity prices due to its lower cost than gas. Moreover, fossil fuels account for 20% of the balancing power market electricity prices.

The current studies have investigated the effect of various energy resources, especially renewable resources, on electricity prices in the day-ahead market. This study aims to determine to what extent electricity generation based on each primary energy resource and the MCP affects Turkey's intraday market electricity prices and the time-dependent variation of this effect.

3. Methodology

3.1. TVP-VAR Model

The TVP-VAR model proposed by Antonakakis & Gabauer (2017) extends the connectedness approach of Diebold & Yılmaz (2014) by using the Kalman filter estimated by Koop & Korobilis (2014) with forgetting factors. The Kalman filter estimated by Koop & Korobolis (2014) allows variances to vary through stochastic volatility. Doing this prevents the loss of irregular or flattened parameters and observations. Thus, the TVP-VAR model can examine dynamic connectedness even at lower frequencies and limited time series data (Antonakakis & Gabauer, 2017: 3). This study used the TVP-VAR (Time-Varying Parameter - Vector Auto-Regressive) model, which dynamically examines the volatility propagation relationship between the series.

$$X_{\mathrm{t}} = \beta_{\mathrm{t}} X_{\mathrm{t-1}} + \mathcal{E}_t \; \mathcal{E}_t \sim n(0, \mathrm{z}_t) \tag{1}$$

$$vec(\beta_{\mathrm{t}}) = vec(\beta_{\mathrm{t-1}}) + \theta_t \theta_t \sim n(0, \mathrm{u}_t) \tag{2}$$

In equations 1 and 2, "X_t, $\mathcal{E}_t$ ve θ_t" are vectors of "n × 1" and "z_t^1, β_t and u_t" are matrices of size "n × n". "$X_t = \sum_{p=1}^{p} \beta_{pt} X_{t-1} + \mathcal{E}_t = \sum_{p=1}^{\infty} N_{rt} \mathcal{E}_{t-r} + \mathcal{E}_t$" represents the Wold moving average in the TVP-VAR model. The vector moving average model forms the basis of the connectedness index (Diebold & Yılmaz, 2012), which is created by using impulse-response generalized functions (ϕ_{prt}^m) developed by Koop et al. (1996) and generalized error estimation variance decompositions ($\acute{Q}_{prt}^m(V)$) developed by Pesaran & Shin (1998). The effect of variable "p" on variable "r" is explained by error estimation variance decomposition. The error estimation variance decomposition is formulated in Equation 3:

$$\mathrm{Q}_{prt}^m(V) = \frac{z_{pr,t}^{-1} \sum_{t=1}^{J-1} (\alpha_p' N_t z_t \alpha_r)^2}{\sum_{r=1}^{n} \sum_{t=1}^{J-1} (\alpha_p N_t z_t N_t' \alpha_p)} \; \widetilde{\mathrm{Q}}_{pr,t}^m(V) = \frac{\mathrm{Q}_{pr,t}^m(V)}{\sum_{r=1}^{n} \mathrm{Q}_{prt}^m(V)} \tag{3}$$

The "α_p" in the equation is the zero vector with its unit at the "p" position ($\sum_{r=1}^{n} \tilde{Q}_{prt}^n(V) = 1$ and $\sum_{p,r=1}^{n} \tilde{Q}_{prt}^n(V) = n$). Equation 4 shows the total connectedness index (TCI), which is the connectedness between variables:

$$\mathrm{C}_t^m(V) = \frac{\sum_{p,r=1,i\neq j}^{n} \widetilde{\mathrm{Q}}_{prt}^m(V)}{\sum_{p,r=1}^{n} \widetilde{\mathrm{Q}}_{prt}^m(V)} \tag{4}$$

The total connectedness index, which does not consider the effect of a variable's lags on itself, can be expressed as the average spillover of all variables over a given asset. The diffusion of total directional connectedness to and from others; is formulated in equations 5 and 6:

$$\mathrm{C}_{p\rightarrow rt}^m(V) = \sum_{r=1,p\neq r}^{n} \widetilde{\mathrm{Q}}_{rpt}^m(V) \tag{5}$$

$$\mathrm{C}_{p\leftarrow rt}^m(V) = \sum_{r=1,p\neq r}^{n} \widetilde{\mathrm{Q}}_{prt}^m(V) \tag{6}$$

Equation 5 shows the total spillover from variable "p" to other variables (r). Equation 6 shows the total spillover from other variables (r) to the variable "p". The difference between the total spread of one variable to the others and the total spillover from the others reveals that variable's position as a net receiver or transmitter of volatility:

$$\mathrm{C}_{pt}^m(V) = \mathrm{C}_{p\rightarrow rt}^m(V) - \mathrm{C}_{p\leftarrow rt}^m(V) \tag{7}$$

In equation 7, if "$(\mathrm{C}_{pt}^m(V) > 0$" the relevant variable is the transmitter of volatility; if "$(\mathrm{C}_{pt}^m(V) < 0$ the relevant variable is the receiver of volatility. The volatility spillover between the two variables is calculated by decomposing the total volatility spillover:

$$NPDC_{pr}(H) = \tilde{Q}_{rpt}(H) - \tilde{Q}_{prt}(H) \tag{8}$$

NPDC refers to the spillover from the variable "p" to the variable "r" as well as the spillover from the variable "r" to the variable "p" (Antonakakis et al., 2019: 9).

3.2. Data

This study aims to dynamically analyse the relationship between Turkey's intraday market electricity prices, day-ahead market electricity prices, and the amount of electricity generated based on primary energy resources. In this context, the daily series is formed by taking the daily average of hourly intraday market electricity prices, day-ahead market electricity prices, and electricity generation amount based on primary energy resources, covering the period from 1 January 2018 to 19 June 2022. New series was created by collecting natural gas and LNG in the "gas" group, dams and rivers in the "hydro" group, lignite, imported coal, asphaltite coal, and hard coal in the "coal" group, and biomass and waste heat in the "bio" group. The TVP-VAR model was applied to the daily data sets created by calculating all series' daily changes (returns)[3]. Data were obtained from the EPİAŞ transparency platform. The descriptions of the data are summarised in Table 1.

Table: 1
Definitions and Use of the Series

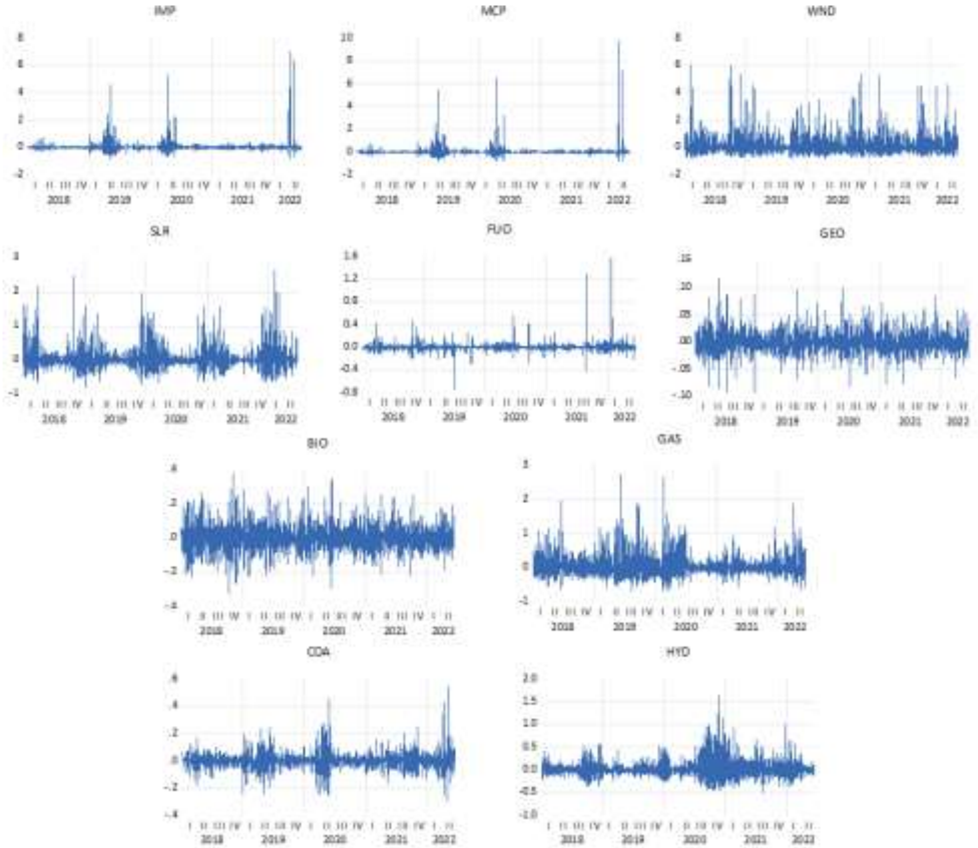
Series	Series Description	Usage of the Series
IMP	Intraday market average daily electricity price[4] (USD)	$(IMP_t - IMP_{t-1}) / IMP_{t-1}$
MCP	Day-ahead market daily average electricity price (USD)	$(MCP_t - MCP_{t-1}) / MCP_{t-1}$
WND	Daily average of wind electricity generation (MWh)	$(WND_t - WND_{t-1}) / WND_{t-1}$
SLR	Daily average of solar electricity generation (MWh)	$(SLR_t - SLR_{t-1})/ SLR_{t-1}$
FUO	Daily average of fuel oil electricity generation (MWh)	$(FUO_t - FUO_{t-1}) / FUO_{t-1}$
GEO	Daily average of geothermal electricity generation (MWh)	$(GEO_t - GEO_{t-1}) / GEO_{t-1}$
BIO	Daily average of biomass electricity generation (MWh)	$(BIO_t - BIO_{t-1}) / BIO_{t-1}$
GAS	Daily average of total electricity generation with natural gas and LNG (MWh)	$(GAS_t - GAS_{t-1}) / GAS_{t-1}$
COA	Daily average of total electricity generation with lignite, imported, asphaltite and hard coal (MWh)	$(COA_t - COA_{t-1}) / COA_{t-1}$
HYD	Daily average of total electricity generation by dams and rivers (MWh)	$(HYD_t - HYD_{t-1}) / HYD_{t-1}$

Figure 1 shows the time-dependent graphs of the daily series.

3 *In this study, three different data sets were used. The first data set covers the period until Covid-19 was declared a pandemic by the World Health Organization (01.01.2018-10.03.2020). The second data set covers the Covid-19 period (11.03.2020-19.06.2022). The third period covers the entire period (01.01.2018-19.06.2022).*

4 *Intraday market electricity prices are given in Turkish Liras (TL) from <https://seffaflik.epias.com.tr/>. Average daily TL prices taken from here have been converted into USD by the closing rate the day before (for weekends, the closing rate on the last trading day of the relevant week) announced by The Central Bank of the Republic of Turkey. For the Central Bank's daily USD/TL prices, the data available at <https://evds2.tcmb.gov.tr/> is used.*

Figure: 1
Time Path Charts of Daily Change Series



When the time path graphs of the daily return series are examined, it is observed that all series are volatile. The volatility in all series increased during the initial periods of Covid-19 and the Russia-Ukraine War. Table 2 shows the descriptive statistics of the series.

Table: 2
Descriptive Statistics of Series

		Average	Max.	Min.	Standard Deviation	Skewness	Kurtosis	JB	ADF
IMP	**BC**[5]	0.02269	4.601334	-0.872561	0.272689	8.01356	114.6931	423876.5**	-3.2973**
	CP[6]	0.03581	7.020098	-0.855442	0.439515	11.25667	157.6944	846138.7**	-33.0121**
	WP[7]	0.02938	7.020098	-0.872561	0.367279	11.45554	182.3086	2219279**	-6.0449**
MCP	**BC**	0.02422	5.458485	-0.890114	0.293884	9.728028	159.5294	828296.7**	-3.3411**
	CP	0.04330	9.763632	-0.893612	0.537058	12.64339	194.4359	1291067**	-32.6255**
	WP	0.03395	9.763632	-0.893612	0.435156	13.60914	246.8721	4089563**	-6.0578**
WND	**BC**	0.17405	6.080987	-0.846694	0.778478	3.072795	18.52064	9277.005**	-24.7915**
	CP	0.16153	5.436042	-0.813376	0.749646	2.984111	16.6017	7639.173**	-21.6769**
	WP	0.16767	6.080987	-0.846694	0.763706	3.032328	17.64482	17064.11**	-29.5931**
SLR	**BC**	0.05180	2.4717	-0.807003	0.344118	2.166665	11.96353	3299.959**	-20.9415**
	CP	0.04454	2.643885	-0.666472	0.322123	2.279042	14.05672	4952.316**	-19.4352**
	WP	0.0481	2.643885	-0.807003	0.333004	2.223788	12.95391	8072.659**	-26.3016**
FUO	**BC**	0.00037	0.46982	-0.741339	0.063961	-0.785237	34.04762	32173.76**	-26.386**
	CP	0.00407	1.567056	-0.411695	0.091215	9.616424	155.5632	818723.1**	-28.9888**
	WP	0.00225	1.567056	-0.741339	0.079037	7.349329	148.3911	1450335**	-23.8563**
GEO	**BC**	0.00067	0.116608	-0.093252	0.021759	0.230155	6.550682	426.7735**	-19.6324**
	CP	0.00015	0.10005	-0.080983	0.021092	0.289247	4.613852	101.7689**	-20.2834**
	WP	0.00040	0.116608	-0.093252	0.021416	0.260071	5.62738	487.218**	-21.176**
BIO	**BC**	0.00389	0.375666	-0.324312	0.086514	0.225185	4.380612	70.20956**	-21.2792**
	CP	0.00383	0.352762	-0.295881	0.070998	0.387476	4.945744	151.8815**	-16.3582**
	WP	0.00386	0.375666	-0.324312	0.078961	0.28875	4.736686	227.4927**	-22.2495**
GAS	**BC**	0.04683	2.732729	-0.713682	0.354801	2.437759	14.36886	5094.344**	-6.7195**
	CP	0.02801	1.867158	-0.676803	0.256555	1.830761	10.44163	2381.668**	-7.2139**
	WP	0.03724	2.732729	-0.713682	0.308694	2.376729	14.97969	11281.52**	-7.1845**
COA	**BC**	0.00139	0.244639	-0.240587	0.051969	-0.065283	6.762969	471.9755**	-8.8969**
	CP	0.00232	0.545926	-0.290159	0.071601	1.305037	13.27159	3889.011**	-11.3982**
	WP	0.00186	0.545926	-0.290159	0.062732	0.97706	13.05794	7129.94**	-11.9563**
HYD	**BC**	0.00848	0.589334	-0.372924	0.124746	0.953918	6.210987	464.4281**	-12.0063**
	CP	0.02069	1.633365	-0.516242	0.222843	1.806596	10.21834	2256.153**	-4.4132**
	WP	0.01471	1.633365	-0.516242	0.181556	1.905265	12.69765	7373.43**	-6.2173**

*Note: The "**" sign indicates significance at the 1% level.*

Table 2 shows that the daily return series are not normally distributed and are stationary. In addition, it is seen that the skewness and kurtosis values of the daily return series of intraday market electricity prices and day-ahead market electricity prices are higher than the other series.

4. Findings

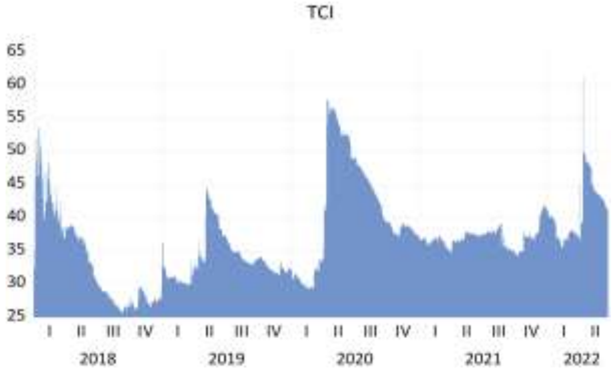
Figure 2 shows the total connectedness of the series. From Figure 2, it is observed that the total interconnectedness between the series has increased after global events such as the US-China trade war (2018-2019; customs duties increased mutually in May 2019), the declaration of Covid-19 as a pandemic (11.03.2020) and the Russia-Ukraine War (24 February 2022).

5 *BC: The period before Covid-19 (01.01.2018-10.03.2020)*

6 *CP: Covid-19 period (11.03.2020-19.06.2022)*

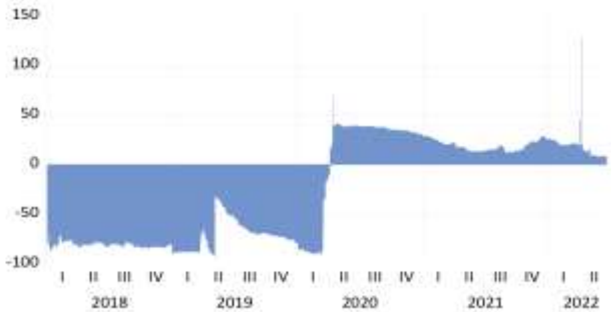
7 *WP: The whole period (01.01.2018-19.06.2022)*

Figure: 2
Time Path Graph of Total Connectedness of Series



It is understood from Figure 3 that the IMP is the net receiver of volatility against other series in total until the Covid-19 period, whereas it is the net transmitter of volatility against other series in total in the Covid-19 period. In addition, the total volatility spillover from IMP to other series reached its highest value by jumping at the beginning of the Russia-Ukraine War.

Figure: 3
The Dynamic Net Volatility Receiver-Transmitter Situation of the Price (IMP)



As a result of dynamic connectedness analysis, it is seen that the connectedness between IMP and other series has increased, especially with Covid-19. Therefore, to see the effect of the Covid-19 pandemic on the average connectedness between IMP and other series, the average connectedness before and during Covid-19 and the entire period was examined separately. The average connectedness for the pre-Covid-19 period is presented in Table 3.

Table: 3
Average Dynamic Connectedness Between Series in the Pre-Covid-19 Period

	IMP	MCP	WND	SLR	FUO	GEO	BIO	GAS	COA	HYD	From
IMP	**5.72**	79.09	1.68	0.56	0.94	0.68	0.91	3.39	5.3	1.72	**94.28**
MCP	1.31	83.86	1.87	0.66	1.11	0.82	0.93	3	5.15	1.29	16.14
WND	1.42	6.77	76.57	1.51	0.47	1.36	1.48	2.86	2.58	4.98	23.43
SLR	0.82	1.97	1.79	86.69	2.95	1.55	0.79	0.93	1.45	1.05	13.31
FUO	0.8	7.09	0.87	0.48	85.5	0.89	1.32	1.29	0.9	0.87	14.5
GEO	0.81	2.43	2.13	1.67	1.57	84.33	1.19	3.16	1.21	1.51	15.67
BIO	0.47	2.38	2.82	0.78	1.27	0.89	87.73	1	1.41	1.25	12.27
GAS	3.17	31.47	2.81	0.71	1.74	1.4	0.76	44.23	6.85	6.85	55.77
COA	3.39	33.58	1.67	1.1	1.66	0.84	1.05	5.76	48.47	2.48	51.53
HYD	5.5	11.52	5.12	1.42	1.14	0.98	0.84	8.71	3.69	61.08	38.92
To	**17.69**	176.29	20.76	8.88	12.86	9.42	9.26	30.1	28.54	22.01	335.81
NET	**-76.59**	160.14	-2.67	-4.43	-1.63	-6.25	-3.01	-25.66	-22.99	-16.91	37.31

According to Table 3, in the pre-Coivd-19 period, the effect of itself on the changes in IMP is 5.72%, the effect of MCP is 79.09%, and the impact of electricity generation amount based on resources is 15.09%. IMP is the net receiver of volatility in pre-Covid-19 (-76.59%). It is seen that the changes in the intraday market prices in the pre-Covid-19 period are explained by the changes in MCP and the changes in the daily electricity generation amount based on resources rather than the changes in themselves. The average connectedness between the series during the Covid-19 period is shown in Table 4.

Table: 4
Average of Dynamic Connectedness Between Series During Covid-19 Period

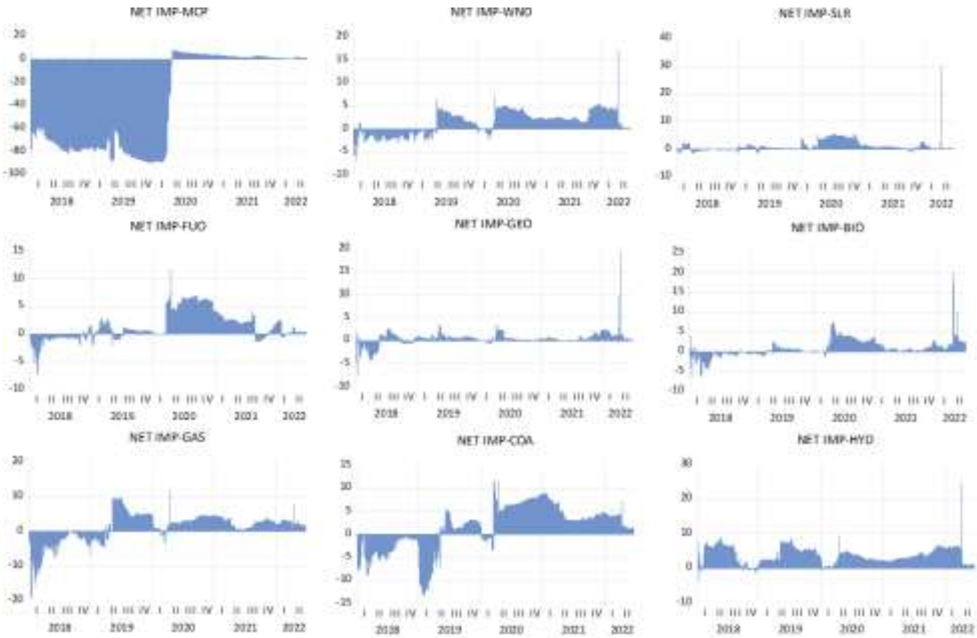
	IMP	MCP	WND	SLR	FUO	GEO	BIO	GAS	COA	HYD	From
IMP	**35.8**	33.45	1.91	0.37	1.75	0.41	0.29	11.71	10.14	4.18	**64.2**
MCP	34.99	37.54	1.41	0.25	1.54	0.43	0.24	11.03	9.67	2.91	62.46
WND	4.1	2.97	73.96	2.13	1.54	2.35	1.35	4.93	1.73	4.94	26.04
SLR	0.74	0.7	4.15	83.73	2.18	1.69	1.41	1.01	1.07	3.31	16.27
FUO	3.02	2.66	1.37	1.4	81.03	0.9	0.85	4.4	2.66	1.71	18.97
GEO	1.09	1.13	2.72	2.23	1.42	84.19	1.64	1.28	1.48	2.83	15.81
BIO	1.15	1.01	1.3	2.09	1.29	1.64	86.71	1.92	1.06	1.83	13.29
GAS	14.08	12.81	2.94	0.67	3.1	0.68	1.15	43.61	13.73	7.22	56.39
COA	13.37	12.16	1.34	0.63	2.11	0.7	1.11	15.37	49.65	3.55	50.35
HYD	7.26	4.8	3.96	3.1	2.55	1.48	0.97	10.48	3.96	61.45	38.55
To	**79.8**	71.69	21.1	12.86	17.48	10.28	9.01	62.13	45.5	32.47	362.33
NET	**15.6**	9.23	-4.94	-3.4	-1.5	-5.53	-4.27	5.74	-4.85	-6.08	40.26

In Table 4, it is seen that in the Covid-19 period compared to pre-Covid-19, the power of the intraday market electricity prices to explain the changes in itself increased (35.8%), the effect of the change in MCP decreased (33.45%), and the impact of the change in electricity generation amount based on resources increased (%30.75). Also, during Covid-19, IMP is the net transmitter of volatility (15.6%). According to the findings, with the experienced global events (such as Covid-19 and the Ukraine-Russia war), the power of the MCP to explain the changes in the intraday market has decreased. Accordingly, the ability to predict the intraday market electricity prices has weakened. In addition, global uncertainties have increased the importance of resource-based electricity generation, which has become more influential on the change in the intraday electricity market prices. In Table 5, the average connectedness for the whole period is highlighted.

Table: 5
Average of Dynamic Connectedness Between Series Over the Whole Period

	IMP	MCP	WND	SLR	FUO	GEO	BIO	GAS	COA	HYD	From
IMP	**19.62**	53.04	2.07	0.65	2.23	0.57	0.54	9.28	8.73	3.28	**80.38**
MCP	15.7	61.86	1.81	0.51	1.67	0.66	0.54	7.29	7.43	2.52	38.14
WND	3.48	5.08	71.95	1.78	1.52	1.97	1.21	4.73	2.96	5.32	28.05
SLR	1.62	1.75	2.11	84.63	2.37	1.45	0.92	1.47	1.67	2.03	15.37
FUO	3.62	5.58	1.51	1	77.36	0.77	0.94	4.53	2.85	1.83	22.64
GEO	0.96	1.7	2.76	2.04	1.24	85	1.22	2.18	1.36	1.53	15
BIO	1.33	1.9	2.19	1.46	1.17	1.2	86.32	1.68	1.51	1.25	13.68
GAS	10.5	21.77	3.24	0.84	3.29	1.04	0.61	41.1	10.86	6.74	58.9
COA	10.27	23.35	1.89	0.98	2.52	0.71	0.68	11.22	45.25	3.13	54.75
HYD	6.93	8.63	4.98	2.15	2.4	1.15	0.78	9.62	4.24	59.13	40.87
To	**54.4**	122.81	22.54	11.42	18.41	9.51	7.45	52	41.6	27.64	367.78
NET	**-25.98**	84.67	-5.51	-3.95	-4.23	-5.49	-6.23	-6.9	-13.15	-13.24	40.86

Figure: 4
Binary Dynamic Connectedness of IMP with Other Series



In the whole period, 19.62% of the change in electricity prices in the intraday market is explained by itself. In comparison, most of the change is defined by the shift in day-ahead market electricity prices (53.04%) and the change in electricity generation amount based on resources (27.34%). In addition, MCP is the net transmitter of the volatility, and other series are the net receivers. When the whole period is analysed, it is seen that the highest total connectedness of the intraday market electricity prices is with the MCP and electricity generated by natural gas and coal, respectively. It has also been determined that the amount of electricity generated by natural gas and coal are the resources with the highest connectedness with MCP. To better understand the relationship between the intraday market electricity prices and other series, the time-dependent graphs of the binary connectedness between IMP and other series are presented in Figure 4.

When the graphs in Figure 4 are examined, it is seen that the direction of the connectedness between the intraday market electricity prices and MCP changed during the Covid-19 period. Before Covid-19, IMP was a net receiver of volatility against MCP, whereas it has become a net transmitter of volatility during the Covid-19 period.

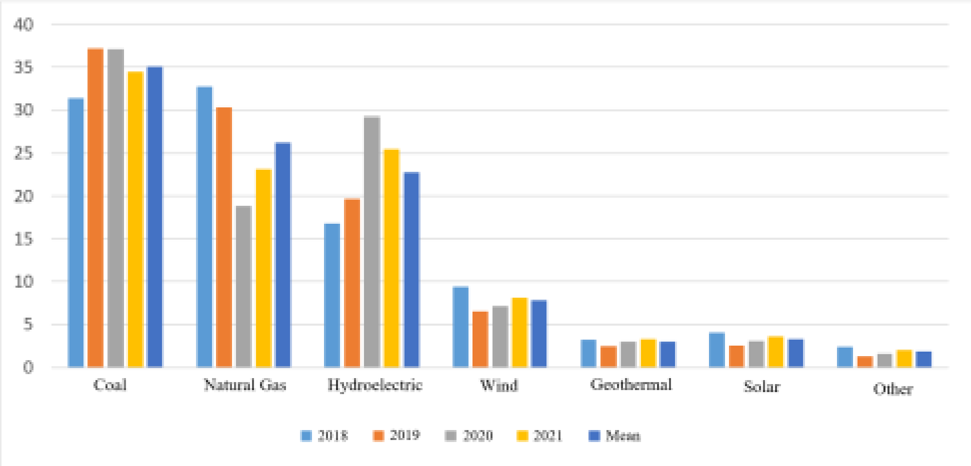
The bilateral net connectedness between IMP and electricity generation amount based on resources varies periodically. While IMP was a net receiver of volatility until mid-2019 against the change in the amount of electricity generated by natural gas and coal, it became a transmitter of volatility in the following period. After March 2020, the bilateral connectedness between IMP and electricity generation by resource either increased or volatility changed direction. In addition, it was observed that the volatility spillover from IMP to renewable energy resources jumped during the Russia-Ukraine War and reached its highest value.

5. Conclusion

The intraday market traded up to 1 hour before the actual time performs an essential function for market participants to balance their short/excess positions, besides bilateral agreements and day-ahead market. Since the intraday market electricity prices are formed after the day-ahead market, they will inevitably be affected by the market clearing price and the primary energy resources from which electricity is generated. This study has tested to what extent the change in electricity prices in Turkey's intraday market is affected by the change in MCP and electricity generation amount based on the primary energy resources. The results show that the day-ahead market electricity price explained 52.07% of the intraday market electricity price change in the period under consideration. It reveals that the day-ahead market price primarily affects the intraday market electricity prices. The explanation level of fossil resources for the change in the intraday market electricity price is 18.45%, and the disclosure rate of renewable energy resources is 7.85%. In other words, fossil resources are more effective than renewable energy in the intraday market electricity price change. Among fossil resources, the level of explaining the price changes of natural gas (8.49%) and coal (8.2%) is higher than renewable energy resources. Although it has the highest share (3.33%) among renewable resources, the level of explaining the price change of hydroelectricity, which has a significant share in total electricity production, remains well below that of natural gas and coal.

Figure 5, derived from TEİAŞ Electricity Statistics and MENR (2022), gives the distribution of total electrical energy generation by resources during 2018-2021. It is seen that the amount of electricity generation with natural gas decreased significantly in 2020 when the Covid-19 Pandemic measures intensified, and the share of hydroelectric power plants and electricity production in the total increased. In 2021, the percentage of natural gas increased again. It is possible to say that this has occurred with the merit order effect due to the decrease in total demand in 2020. The power of natural gas and coal to explain the change in the intraday market electricity price also confirms the merit order effect.

Figure: 5
Distribution of Electricity Generation by Resources (2018-2021)



The paper's findings show that the volatility in the intraday market electricity prices changes depending on time and critical global developments. After Covid-19 was declared a pandemic, the net connectedness of the intraday market electricity prices with MCP decreased and changed direction. It shows that the effect of the market clearing price, which is the reference price for the electricity markets, on the intraday market electricity prices has decreased relatively with Covid-19. The volatility relationship that changes with MCP and the amount of generation based on primary energy resources over time reveals the dynamic structure of the intraday market electricity prices. It also indicates that the intraday market electricity price can affect the power plants' MCP and generation amount. Considering the dynamic structure of the intraday market, electricity prices would be better when making production/supply planning and bidding in the day-ahead market.

References

Antonakakis, N. & D. Gabauer (2017), "Refined Measures of Dynamic Connectedness based on TVP-VAR", *MPRA Paper* 78282, University Library of Munich, Germany.

Antonakakis, N. et al. (2019), "Oil And Asset Classes Implied Volatilities: Dynamic Connectedness and Investment Strategies", <https://ssrn.com/abstract=3399996>, 30.06.2022.

Apergis, N. et al. (2020), "Dependence Structure in the Australian Electricity Markets: New Evidence from Regular Vine Copulae", *Energy Economics*, 90, 1-14.

Asceric, A. et al. (2022), "Correlation of Day-Ahead Electric Energy Market Price with Renewable Energy Sources Generation and Load Forecast, Advanced Technologies", in: *Advanced Technologies, Systems, and Applications VI* (99-109).

Bento, P.M.R. et al. (2018), "A Bat Optimized Neural Network and Wavelet Transform Approach for Short Term Price Forecasting", *Applied Energy,* 210, 88-97.

Berk, İ. & E. Torun (2019), "Testing Merit-Order Effect in Turkey's Electricity Market: The Effect of Wind Penetration on Day-Ahead Electricity Prices", *Akdeniz IIBF Journal*, 19(1), 133-156.

Cervone, A. et al. (2014), "Electricity Price Forecast: A Comparison of Different Models to Evaluate the Single National Price in the Italian Energy Exchange Market", *International Journal of Energy Economics and Policy*, 4(4), 744-758.

Chan, K.F. et al. (2008), "A new approach to characterizing and forecasting electricity price volatility", *International Journal of Forecasting*, 24, 728-743.

Ciarreta, A. & A. Zarraga (2016), "Modeling Realized Volatility on the Spanish Intra-Day Electricity Market", *Energy Economics,* 58, 152-163.

Clo, S. et al. (2015), "The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices", *Energy Policy*, 77, 79-88.

Devir, K. (2017), *Türk Elektrik Piyasasının İşleyişi*, Bursa: Dora Publishing.

Diebold, F.X. & K. Yılmaz (2014), "On the network topology of variance decompositions: measuring the connectedness of financial firms", *Journal of Econometrics*, 182(1), 119-134.

Dong, S. et al. (2019), "Volatility of electricity price in Denmark and Sweden", *Energy Procedia,* 158, 4331-4337.

EPİAŞ (N/A), <https://seffaflik.epias.com.tr/transparency/index.xhtml>, 21.06.2022.

EXIST (2022), *Participant Count Based Upon License Type*, <https://seffaflik.epias.com.tr/transparency/piyasalar/genel-veriler/lisans-tipine-gore-katilimci-sayisi.xhtml>, 30.06.2022.

EXIST (2022a), *Power Futures Market Introduction*, <https://www.epias.com.tr/en/introduction/>, 30.06.2022.

EXIST (2022b), *Intraday Market Introduction,* <https://www.epias.com.tr/en/intra-day-market/introduction/>, 30.06.2022.

EXIST (2022c), *Intraday Market General Principles,* <https://www.epias.com.tr/en/intra-day-market/general-principles/>, 30.06.2022.

Fernandez, J.M.R. et al. (2021), "Impact of Domestic PV Systems in the Day-Ahead Iberian Electricity Market", *Solar Energy*, 217, 15-24.

Gianfreda, A. et al. (2019), *The RES-Induced Switching Effect Across Fossil Fuels: An Analysis of Day-Ahead and Balancing Prices*, <https://www.iaee.org/energyjournal/article/3316>, 30.06.2022.

Girish, G.P. & S. Vijayalakshmi (2013), "Determinants of Electricity Price in Competitive Power Market", *International Journal of Business and Management*, 8(21), 70-75.

Guo, X. et al. (2020), "A Short-Term Load Forecasting Model of Multi-Scale CNN-LSTM Hybrid Neural Network Considering The Real-Time Electricity Price", *Energy Reports*, 6, 1046-1053.

Gürtler, M. & T. Paulsen (2018), “The Effect of Wind and Solar Power Forecasts on Day-Ahead and Intraday Electricity Prices in Germany”, *Energy Economics*, 75, 150-162.

Huang, C.J. et al. (2020), “A Novel Hybrid Deep Neural Network Model for Short-Term Electricity Price Forecasting”, *International Journal of Energy Research*, 45(2), 2511-2532.

Karakatsani, N.V. & D.W. Bunn (2010), “Fundamental and Behavioural Drivers of Electricity Price Volatility”, *Studies in Nonlinear Dynamics & Econometrics*, 14(4), 1-42.

Ketterer, J.C. (2014), “The impact of wind power generation on the electricity price in Germany”, *Energy Economics*, 44, 270-280.

Koop, G. & D. Korobilis (2014), “A new index of financial conditions”, *European Economic Review*, 71, 101-116.

Koop, G. et al. (1996), “Impulse Response Analysis in Nonlinear Multivariate Models”, *Journal of Econometrics*, 74(1), 119-147.

Kuo, P.H. & C.J. Huang (2018), “An Electricity Price Forecasting Model by Hybrid Structured Deep Neural Networks”, *Sustainability*, 10(4), 1-17.

Li, W. & D.M. Becker (2021), “Day-Ahead Electricity Price Prediction Applying Hybrid Models of LSTM-Based Deep Learning Methods and Feature Selection Algorithms Under Consideration of Market Coupling”, *Energy*, 237, 121543.

Marcos, R.A.D. et al. (2019), “Electricity Price Forecasting in the Short Term Hybridising Fundamental and Econometric Modelling”, *Electric Power Systems Research*, 167, 240-251.

Matsumoto, T. & M. Endo (2021), “Electricity Price Forecast Based on Weekly Weather Forecast and Its Application to Arbitrage in the Forward Market”, *11th International Conference on Power, Energy and Electrical Engineering (CPEEE)*, Shiga, Japan, 104-111.

MENR (2022), *Electricity*, <https://enerji.gov.tr/bilgi-merkezi-enerji-elektrik#:~:text=2021%20y%C4%B1l%C4%B1nda%20elektrik%20%C3%BCretimimizin%2C%20%31,g%C3%BCc%C3%BC%20100.667%20MW'a%20ula%C5%9Fm%C4%B1%C5%9Ft%C4%B1r>, 30.06.2022.

Mirakyan, A. et al. (2017), “Composite Forecasting Approach, Application for Next-Day Electricity Price Forecasting”, *Energy Economics*, 66, 228-237.

Mulder, M. & B. Scholtens (2013), “The Impact of Renewable Energy on Electricity Prices in the Netherlands”, *Renewable Energy*, 57, 94-100.

Nieta, A.A.S.D.L. & J. Contreras (2020), “Quantifying the Effect of Renewable Generation on Day-Ahead Electricity Market Prices: The Spanish Case”, *Energy Economics*, 90, 104841.

Niza, E.C. et al. (2022), “A Volatility Spillover Analysis with Realized Semi(co)variances in Australian Electricity Markets”, *Energy Economics*, 111, 106076.

Paraschiv, F. et al. (2014), “The Impact of Renewable Energies on EEX Day-Ahead Electricity Prices”, *Energy Policy*, 73, 196-210.

Pereira, A.J.C. & J.T. Saraiva (2013), “Long Term Impact of Wind Power Generation in the Iberian Day-Ahead Electricity Market Price”, *Energy*, 55, 1159-1171.

Pesaran, H.H. & Y. Shin (1998), “Generalized Impulse Response Analysis In Linear Multivariate Models”, *Economics Letters*, 58(1), 17-29.

Qiao, W. & Z. Yang (2020), “Forecast the Electricity Price of U.S. Using a Wavelet Transform-Based Hybrid Model”, *Energy*, 193, 116704.

Rajan, P. & K.R.M.V. Chandrakala (2021), "Statistical Model Approach of Electricity Price Forecasting for Indian Electricity Market", 2021 IEEE Madras Section Conference (MASCON), Chennai, India, 1-5.

TEİAŞ (2022), *About Us*, <https://www.teias.gov.tr/en-US>, 30.06.2022.

TEİAŞ (N/A), <https://www.teias.gov.tr/turkiye-elektrik-uretim-iletim-istatistikleri>, 30.06.2022.

Terzic, I. et al. (2021), "Modelling and Forecasting Volatility on Electric Power Exchange SEEPEX", *Management: Journal of Sustainable Business and Management Solutions in Emerging Economies*, https://doi.org/10.7595/management.fon.2021.0002.

Thoenes, S. (2011), "Understanding The Determinants of Electricity Prices and The Impact of The German Nuclear Moratorium in 2011", *EWI Working Paper*, 11/06, 1-30.

Tschora, L. et al. (2022), "Electricity Price Forecasting on the Day-Ahead Market Using Machine Learning", *Applied Energy*, 313, 118752, 1-14.

Uğurlu, U. et al. (2018), "Electricity Price Forecasting Using Recurrent Neural Networks", *Energies*, 11(5), 1-23.

Ulgen, T. & G. Poyrazoğlu (2020), "Predictor Analysis for Electricity Price Forecasting by Multiple Linear Regression", *2020 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)*, Sorrento, Italy, 618-622.

Würzburg, K. et al. (2013), "Renewable Generation and Electricity Prices: Taking Stock and New Evidence for Germany and Austria", *Energy Economics*, 40, S159-S171.

Xie, X. et al. (2018), "The Day-Ahead Electricity Price Forecasting Based on Stacked CNN and LSTM", in: Y. Peng et al. (eds.), *International Conference on Intelligent Science and Big Data Engineering*, 11266, 216-230.

Yang, W. et al. (2022), "A Novel Machine Learning-Based Electricity Price Forecasting Model Based on Optimal Model Selection Strategy", *Energy*, 238(C), 121989.

Yarıcı, M. (2018), *EPİAŞ Elektrik Piyasaları Eğitim Sunumları: Gün Öncesi Piyasası*, İstanbul: EPİAŞ Yayınları.

Yılmaz, E. & P.P. Cowley (2022), "Enerji Tüketimi ve Ekonomik Büyüme İlişkisine Ekonometrik Yaklaşım", *Journal of Academic Researches and Studies*, 14(26), 59-74.

Zareipour, H. et al. (2007), "Electricity Market Price Volatility: The Case of Ontario", *Energy Policy*, 35(9), 4739-4748.

Zhou, S. et al. (2019), "An Optimized Heterogeneous Structure LSTM Network for Electricity Price Forecasting", *IEEE Access*, 7, 108161-108173.